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Interdisciplinary Irrigated Precision Farming Research

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Abstract. The USDA-Agricultural Research Service and Colorado State University are conducting an interdisciplinary study that focuses on developing a clearer scientific understanding of the causes of yield variability. Two years of data have been collected from two commercial center pivot irrigated fields (72 and 52 ha). Cooperating farmers manage all farming operations for crop production and provide yield maps of the maize grown on the fields. The farmers apply sufficient inputs to minimize risk of yield loss. The important variables for crop production have been sampled at a grid spacing of 76 m for two seasons. A spatial auto-regressive model was fitted to the data to determine the critical factors affecting yield variability. Thirty one layers of data were included in the analysis, and a total of over 140,000 models were examined. Up to five predictors were used in each model. Variability in water application, nitrate nitrogen, organic matter, phosphorus, topology, percent silt and soil electrical conductivity were significant in explaining the yield variability for Field 1. Variability in water application, ammonium, nematodes, percent clay, insects, potassium, soil electrical conductivity, and topology were significant in explaining the yield variability for Field 2. The tentative conclusion is that the potential economic benefit of site specific management is small where the farmer's management tolerance for risk is low. The potential of site specific management is in reducing the cost of inputs and environmental impact, but could increase risk.

Keywords: spatial statistics, center-pivot irrigation system, variable rate application, on-farm research

Introduction

Precision farming (PF) or site specific management is currently promoted by several sectors of agribusiness. The concept of precision farming is to apply the right amount of inputs at the right time on the right area. Farmers are using combines with GPS and grain yield monitors to generate maps of spatial yield variability within fields. Many fertilizer dealers offer variable application of fertilizers and chemicals using specialized equipment. Precision farming is not just the use of high-tech equipment, but the acquisition and wise use of information obtained from that technology (Vanden Heuvel, 1996). The long term thrust of our research effort is to evaluate the impacts of PF on water quality and the economic feasibility of PF under irrigated conditions. The objectives are to quantify the causes of yield variability and the economic feasibility and environmental benefits of precision farming (Fleming *et al.*, 1998). The farmers' willingness to change their management strategy based on the scientific evidence that they can decrease input costs but not significantly increase risk is an important consideration.

Fertility management is generally assumed to have the potential to increase or maintain production with variable rates of fertility input. Few studies have attempted to determine the factors that contribute to yield variability. Sudduth *et al.* (1996) studied the relationship between yields, soil properties, and site properties, and site properties on a spatial basis to predict spatial crop yields. They concluded that understanding yield variability was difficult because of the number of inter-related factors that affect yield. Many such studies relating yield to a single or a few parameters are reported, but virtually none that examine the impact of the range of parameters included in this study.

An extensive literature base for PF has been compiled in the proceedings for six international Precision Agriculture (PA) Conferences held in Minneapolis, Minnesota in the even years since 1992. The European Precision Agriculture Conferences held in UK and Denmark in 1997 and 1999, respectively, have added to the literature base. Robert (1999) identified the research needs for PA and observed that PA is a new holistic approach to agricultural management and it is progressively evident that we are still missing many parts of the whole system. He expressed a need for expansion of the horizon of disciplines in PA research. Bullock (1999) noted that the technological aspects of PF are becoming better known, but how to use this technology to increase farm profits remain ripe for research. He contends that we know relatively little about whether and how different soil types should be planted and fertilized at different rates. The National Research Council (1997) studied the needs for Precision Agriculture Research in the 21st Century. They observed that precision agriculture requires new approaches to research that are designed explicitly to improve understanding of the complex interactions between multiple factors affecting crop growth and farm decision making.

Sampling strategies and analysis techniques are needed for integration into a decision support system that determines the appropriate scale for implementing variable rate technology. A multidisciplinary team including soil fertility scientists, crop scientists, weed scientists, entomologists, plant pathologists, systems engineers, remote sensing scientists, GIS experts, irrigation engineers, agricultural economists, and statisticians is working together to systematically gain a better understanding of precision farming. Buchleiter *et al.* (1997) presented the details of the project organization and site selection. The specific objective of this paper was to evaluate the most important factors affecting yield variability under the existing farm management and the potential for use of PF. There was no intention to develop a model for predicting yield. Two co-operating farmers using high levels of inputs to obtain maximum yields were managing their own maize production and provided us with the yield data from two center pivot irrigated fields. We also observed how their management strategies were influenced by the results of our data collection and analysis.

Materials and methods

Aerial photographs of the two center pivots obtained by the USDA Farm Service Agency in 1992–1995 and the USDA-Natural Resource Conservation Service (NRCS) soils maps were used to select fields that exhibited significant crop and soil variability. Topography maps with 30 cm contour interval were made with the assistance of the NRCS. Field data were collected by the scientists from each discipline, sampling their respective parameters within each cell in the 76×76 m grid. Early in the design of this study (1995) a grid type design was agreed upon. One main goal of the participants was to measure all quantities across the entire field. In our study many different quantities were measured across the field with different levels of time and energy required to collect each observation. For example, yield is automatically monitored on a very fine scale. In contrast, it is expensive and labor intensive to measure soil characteristics at many locations on the field. In addition, at the time the study was designed, the scale of spatial correlation for many of the predictors was unknown, especially for Eastern Colorado corn fields. For example, in this area insect infestations were typically measured via 1 trap per field as opposed to full field coverage via many traps. To account for these contrasting goals and to operate within the economic constraints of the project, the project design team recommended a 76 m $\times$ 76 m grid. It was recognized at the the time of design that this scale might be too large to accurately reflect the spatial correlations for some predictors; however, this scale allowed for measurement of all variables for every grid cell in each field. Additional information about the scale of some of these predictors is now available (McBratney and Pringle, 1997) and this type of information would be useful in determining the optimal grid size for future studies.

Soils data

The soils were sampled for fertility at randomly selected sites within each of the grid cells in April 1997 and March 1998. The surface 30 mm was analyzed for NO_3—N, NH_4—N, P, K, Zn, pH, organic matter and texture. Subsoil samples for 0.3–0.6, 0.6–0.9 and 0.9–1.2 m increments were analyzed for NO_3—N and NH_4—N. A Geonics Limited EM38[1] conductivity sensor was used to generate an electromagnetic conductivity map in the spring of 1997 for both fields. Electrical conductivity data were also collected in the spring of 1998 using the Veris[1] soil mapping system.

Weed data

The weed seedling population was sampled after post emergence spraying to estimate the weed population that competed with the crop (Wyse-Pester *et al.*, 1998). Seedlings were identified and counted by species in a 0.15 m band over 1.52 m of crop row. Seedlings were sampled at the center of each grid cell and at a randomly selected site between adjacent center points within a row. Major species were pigweed (*Amaranthus retroflexus* L.), nightshade (*Solanum sarrachoides* Sendtner), lambsquarter (*Chenopodium album L.*), and field sandbur (*Chenchrus incertus* M. A. Curtis). Since weed species differ in the ability to compete with maize, the total competitive load (Coble, 1986) was calculated for each quadrat. Total competitive load (TCL) is a weighted sum of weed density with the density of a species weighted by an index of the relative competitiveness of that species:

$$\mathrm{TCL} = \sum_{i=1}^{n} CI_i D_i \tag{1}$$

where n is the number of species, D_i is the density of species i, and CI_i is the index of relative competitiveness of species i; $0 \le CI_i \le 1$.

Nematode data

Nematodes that attack maize are obligate parasites that must feed on living plants to complete their life cycle. Nematode populations were sampled on the 76×76 grid system one week after maize harvest. A soil profile sample of 50 mm. diameter by 100 mm depth was taken in the maize row at each observation site. Nematodes were extracted from 100 g of soil with standard centrifuge flotation procedure. From the 100 g soil sample, the numbers of nematodes by species were counted. Since the conventional method in nematology is to express the number of nematodes per 100 cc soil sample, our data are expressed in this manner. *Helicotylenchus* (spiral), *Tylenchorhnchus capitatus* (stunt), and *Pratylenchus scriberi* and *P. neglectus* (lesion) nematodes were present in Fields 1 and 2 in 1997 and 1998.

Insect data

Adult activity of locally important pest insects was measured. Pheromone traps were monitored weekly during the flight periods of European corn borer, *Ostrinia nubilalis* (Hübner), and western bean cutworm, *Richia albicosta* (Smith). Western corn rootworm, *Diabrotica virgifera virgifera* LeConte, adults were also monitored with traps containing the attractant 4-methoxycinnamaldehyde. One trap was located in each grid cell and more intense sampling was done in at least one quarter of each field. A total of 375 and 359 trap locations were used over the two study fields for 1997 and 1998 respectively.

Climatic and irrigation data

Center pivot irrigation systems with low-pressure applicators and a large sprinkler on the outer end of the lateral to irrigate the corners were used on both fields. A weather station was located adjacent to each field to measure solar radiation, temperature, vapor pressure, wind run, and precipitation. The data were used to calculate daily evapotranspiration (ET) for soil water budgeting purposes. Six recording rain gauges were placed around the periphery and one at the center of each field to assess spatial variability of rainfall. Records of the irrigation timing and amount of water applied were maintained throughout the irrigation season.

Since it is infeasible to physically collect irrigation depths across the fields for all irrigations, depths computed from a simulation program that had been verified by field catch can data were used to map total water application (Jordan *et al.*, 1998). Figure 1 is an example of the seasonal computer simulated depths. The average application depth was computed for each small radial cell. The variation in application depths is a result of the non-uniformity along the radial irrigation lateral, differences in elevation and the intermittent operation of the large sprinkler at the outer end of the lateral. The large sprinkler applied water beyond the boundary of the circle, but that area is not included in the analysis. An additional variation in the seasonal totals is the result of moving the system to the starting point without irrigating following a rain. The fact that several values of water application were calculated (radial cells) within each 76 m $\times$ 76 m cell allowed calculation of the average, maximum, minimum, and standard deviation of seasonal water applied in each grid cell. The water budget was calculated at each grid point to determine locations of excess and deficit irrigation throughout the season (Morton *et al.*, 1998).

Yield data

The co-operators harvested both fields with combines equipped with yield monitors and GPS units. A base GPS unit that broadcast differential signals to increase the spatial accuracy was installed in the area. Yield data were processed and mapped with Farmers' Software Harvest Mapping System on a Map Info platform. The 1997 average maize yields were 10.9 and 13.0 t/ha for Fields 1 and 2, respectively. In 1998, the average maize yields were 8.8 and 12.2 t/ha for Fields 1 and 2, respectively.

The average yield data were summarized from the individual yield monitor observations within each grid cell. In 1997, a total of 58,474 and 42,338 data points were collected in 120 and 84 cells on Field 1 and 2, respectively. In 1998, 44,737 and 40,788 data points were collected in 116 and 75 cells on Field 1 and 2, respectively.

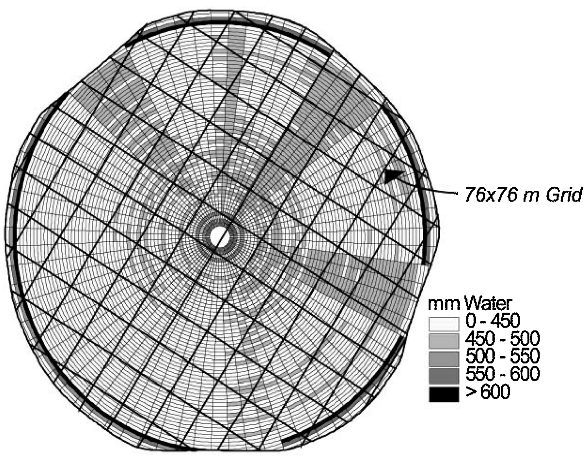

Figure 1. Example of computer simulated seasonal application depths for the 1998 irrigation season on Field 1.

Data layers for statistical analysis

All variables included in the analysis are summarized in Tables 1 and 2. The yield data had an average of 440 and 476 individual combine measured points in each 76 m × 76 m grid cell for Fields 1 and 2, respectively. The seasonal irrigation depths were simulated for an average of 86 to 103 points within each large grid cell for Field 1 and 2 (Jordan *et al.*, 1998) (Figure 1). The minimum, maximum and standard

Table 1. Description and range across the cells of yield, water, insect, and weed variables for each cell used in the statistical model

			Field 1		Field 2	
Variable	Units	Year	Min	Max	Min	Max
Yield						
Cell average	t/ha	1997	8.42	12.14	10.04	13.97
		1998	5.98	10.11	9.03	14.84
Cell minimum	t/ha	1997	2.20	9.67	2.21	11.37
		1998	2.20	7.89	2.20	13.18
Cell maximum	t/ha	1997	11.70	18.73	13.48	17.85
		1998	9.28	17.50	12.16	18.59
Cell standard deviation	t/ha	1997	2.20	9.67	0.52	3.45
		1998	0.61	2.51	0.62	2.98
Maize population	ha^{-1}	1997	60,000	100,000	75,000	100,000
		1998	34,000	95,000	52,000	100,000
Water application						
Cell average	mm	1997	549	982	427	1338
		1998	422	649	393	531
Cell minimum	mm	1997	163	568	156	731
		1998	162	508	38	505
Cell maximum	mm	1997	610	2,294	608	2,687
		1998	436	1,924	457	619
Cell standard deviation	mm	1997	22	487	8	657
		1998	7	457	8	122
Total Competitive Weed Load	(ND)	1997	0.0	22.9	0.0	1.0
		1998	0.0	7.3	0.4	0.4
European corn borer—average	count	1997	0.0	5.0	0.1	4.4
		1998	0.0	14.0	0.0	1.0
Western bean cutworm—total	count	1997	0	326	0	89
		1998	4.0	163	0.0	97
Western corn rootworm—total	count	1997	0	4	0	5
		1998	0.0	6.0	0.0	6.0
Nematodes						
Total stunt/100cm^3		1997	0	630	0	884
		1998	0	383	0	731
Spiral		1997	0	606	0	391
		1998	0	309	0	1543
Lesion		1997	0	156	0	246
		1998	0	148	0	119
Total		1997	0	852	0	893
		1998	0	497	0	1727

Table 2. Description and range of soil variables across the cells used in statistical model*

			Field 1		Field 2	
Variable	Units	Year	Min	Max	Min	Max
Soil texture						
Sand	%	Both	71.6	93.6	68.0	91.6
Silt	%	Both	0.4	10.8	2.4	18.8
Clay	%	Both	4.0	20.4	5.0	16.0
Phosphorous	mg kg^{-1}	1997	4	54	5	23
		1998	5	103	4	42
Potassium	mg kg^{-1}	1997	93	417	125	291
		1998	87	314	108	338
Nitrate nitrogen	mg kg^{-1}	1997	4	59	4	25
		1998	1	28	4	30
Zinc	mg kg^{-1}	1997	2.2	8.1	1.3	3.5
		1998	2.3	7.5	1.2	7.3
Ammonium nitrogen	mg kg^{-1}	1997	2	9	1	5
		1998	3	10	3.3	7.2
Organic matter	%	1997	0.6	1.7	0.7	1.4
		1998	0.5	1.6	0.7	1.4
pH	(ND)	1997	6.8	8.1	7.1	8.0
		1998	6.9	7.9	7.2	8.1
Elevation						
Cell mean	m	Both	1354.9	1357.1	1341.8	1349.1
Cell minimum	m	Both	1353.5	1356.8	1341.2	1348.5
Cell maximum	m	Both	1354.1	1357.4	1342.4	1349.4
Cell std. deviation	m	Both	0.04	0.56	0.02	1.00
Soil electrical (EM) conductivity (0–1.0 m)	ms/m^2	1997	15.5	58.5	9.8	35.5
Shallow soil electrical(Veris) conductivity (0–0.3 m)	ms/m^2	1998	7.8	20.9	5.7	13.8
Deep soil electrical (Veris) conductivity (0–1.0 m)	ms/m^2	1998	10.8	42.9	11.5	28.7

*The soil parameters are from the top 300 mm of the soil profile.

deviation are reported for each cell based on the combine measured yields and simulated irrigation depths. The maximum and minimum for each row of data are the maximum and minimum for each of the variables calculated or observed in the individual cells. Because nutrients, soil texture, plant populations and pest densities were sampled at a single point within each 76 m × 76 m grid cell, no within cell statistics could be calculated. The yield for Field 1 was significantly lower for 1998 because of hail damage. The soil texture and elevation obviously did not change, the EM38 soil electrical conductivity data were collected only in 1998, and Veris soil electrical conductivity data were collected only in 1997.

Model development

The primary goal of the analysis was to determine which predictors X estimated yield, Y. X is a matrix with the first column equal to one and the other columns corresponding to the predictors. In an effort to find the simplest model possible, we first fit a standard regression model (e.g., Weisberg, 1985),

$$Y = X\beta + \varepsilon, \quad \varepsilon \sim N(0, \sigma^2), \tag{2}$$

where β is the vector of regression coefficients, ε is the error term, assumed to follow a normal distribution with mean 0 and variance σ^2. The regression model was found to be inappropriate because the residuals were spatially correlated. The residuals must be independent to satisfy the assumptions of the regression model (Eq. 2). Ignoring spatial correlation can cause important predictors to be missed in the analysis.

To account for the spatial relationship between the observations, we chose an autoregressive spatial model (Upton and Fingleton, 1985). The model also accounts for autocorrelation in the response as well as autocorrelation in the predictors. Under this model, yield for a particular grid cell may be correlated with the yield at neighboring cells, and the predictors for a particular grid cell may be correlated with the predictors observed in the surrounding grid cells. The autoregressive model is defined

$$(I - \rho W)Y = (I - \rho W)X\beta + \varepsilon, \varepsilon \sim N(0, \sigma^2) \tag{3}$$

where I is the identity matrix and ρ is the spatial autoregressive parameter, and W is the spatial weights matrix corresponding to a first order neighborhood. This means that the yield observations (Y) in the grid cells immediately north, south, east, and west of grid cell i are used to predict the observation in grid cell i to correct for the spatial dependency. The ith element of the vector WY is the average of the Y values for the neighbors of observation i to correct for the spatial dependence. Figure 2 shows the yield and the spatially adjusted yield in Field 1 in 1997.

The parameter estimates for the autoregressive model can be interpreted in much the same way that the parameter estimates of a standard regression model are interpreted. Each predictor X_i is adjusted by the average of the X_i's for the neighbors and the yield for observation i is adjusted by the average of the yield for the neighbors. If $\hat{\beta}$ is positive, then as the adjusted predictor X_i increases, the adjusted yield also increases (while all other predictors are held fixed). A likelihood ratio test is used to determine whether the

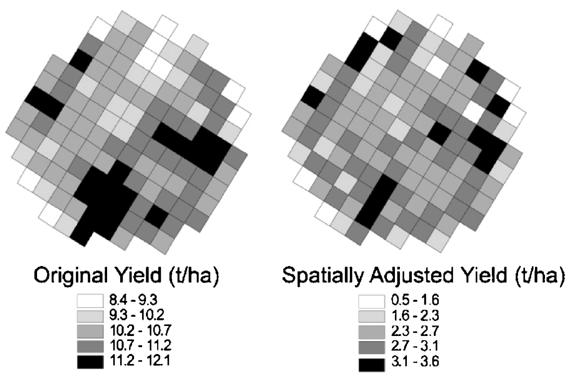

Figure 2. An example of the adjustment of original yield data to spatially adjust yield values for the spatial autoregressive model.

parameter ρ is significantly different from zero. If ρ is significantly different from zero, this indicates significant spatial correlation. In other words, observation i's neighbors are good predictors of the yield for observation i.

The second goal of the analysis was to determine which set of predictors produced the best estimates of yield. We fit separate models for each year and each field. An extensive model selection effort was undertaken using the corrected Akaike information criterion (AICC) (Hurvich and Tsai, 1989). Thirty one possible predictors of yield were considered for inclusion in the models for 1997, twenty three possible predictors of yield were considered for inclusion for 1998 Field 1, and thirty possible predictors of yield were considered for inclusion for 1998 Field 2. This difference in number of predictors stems from the fact that some predictors were not measured in 1998 and there were also some missing values. Several sets of predictors (the irrigation predictors, the conductivity predictors, and the elevation predictors) were highly correlated. Since highly correlated predictors can produce unstable estimates of the parameters, only one of the predictors from each of these sets of predictors was allowed to enter into each model. Similarly, the texture predictors sum to 100%, so at most two of the predictors were allowed to enter into each model. All models with up to five predictors were examined. For each field in 1997, over 100,000 models were considered and in 1998, over 40,000 models were considered. The final models that were chosen had small AICC values compared to other models being considered and contained the predictors that appeared most frequently in the top models as measured by AICC. This model selection approach does not avoid all of the potential problems related to data mining (Burnham and Anderson, 1998), but it does ensure some sense of reliability because the final predictors appeared in most of the top models. In interpreting the models described below, the focus should be on the selected predictors that are included in the model as opposed to the p-values of the regression coefficients.

Model results

The yield distribution varied between years on the two fields. The correlation between 1997 and 1998 yields in Field 1 was relatively strong ($r = 0.58$), while the correlation for Field 2 was weak and negative ($r = -0.06$) (Figure 3).

The coefficients for the best model for Field 1 are shown in Tables 3 and 4. (Note that the p-values for β do not account for the uncertainty in estimating ρ. This also holds for Tables 5 and 6.) The best predictors of yield in 1997 were average deep conductivity (Veris), pre-season nitrate nitrogen, organic matter, phosphorous, and minimum seasonal water application. The best model explained 72% of the variability in the response, ($R^2 = 0.72$) with 45% of the variability in yield explained by the spatial correlation between the yield observations and an additional 27% of the variability in yield explained by the predictors. In 1998, the average seasonal water application per cell, minimum elevation, percent silt, and average deep conductivity were the best predictors of yield. This model explained 72% of the variability in the response ($R^2 = 0.72$) with 40% of the variability in yield explained by the spatial correlation between the yield observations and an additional 32% of the variability in yield explained by the predictors. Note that R^2 increases as the number of predictors in a model increased.

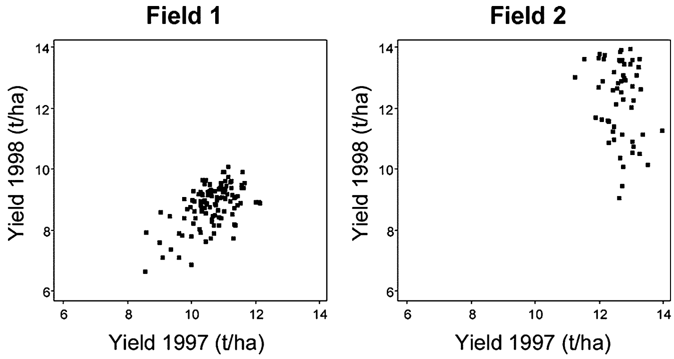

Figure 3. Comparison of the yields in 1997 and 1998.

The coefficients for the best model for Field 2 are shown in Tables 5 and 6. In 1997, the best predictors of Field 2 yield were average shallow conductivity, ammonium, total nematodes for the season, and minimum water application. The model explained 46% of the variability in yield with 24% explained by spatial correlation of the yield. In 1998, the predictors included in the best model were maximum elevation within the 76 m $\times$ 76 m cell, percent clay, average western bean cutworm (WBC) infestation, average deep conductivity (Veris), and potassium. The model explained 87% of the variability in yield, with 61% of the variability explained by spatial correlation.

For both fields and both years, the spatial parameter, ρ was positive and significantly different from zero (Tables 3–6). For a given observation, i, this indicates that as the average yield for the neighboring observations increases, the average yield for observation i also increases (with all other predictors held fixed). Standard diagnostics for the selected models did not indicate any violations of the assumptions of the autoregressive model.

Implications of model for site specific application

The water terms for each of the fields in 1997 and for Field 1 in 1998 were significant in explaining yield variability. The lower yields were on the periphery of the field where

Table 3. Spatial autoregressive grain yield model coefficients for Field 1, 1997

	$\hat{\beta}$	Standard error	p-value
Intercept	8.100	0.37000	<0.0001
Deep conductivity	0.0440	0.00830	<0.0001
Nitrate nitrogen	−0.0140	0.00560	0.0232
Organic matter	1.1000	0.27000	0.0001
Phosphorus	−0.0240	0.00560	0.0001
Min. season water	0.0020	0.00055	0.0002

Note: $\hat{\rho} = 0.71$, likelihood ratio test $= 57.40$, p-value < 0.0001.

Table 4. Spatial autoregressive grain yield model coefficients for Field 1, 1998.

	$\hat{\beta}$	Standard error	p-value
Intercept	464.00	157.000	0.0039
Ave season water	−0.017	0.002	<0.0001
Min elevation	−0.330	0.120	0.0052
Silt content	0.045	0.023	0.0472
Deep conductivity	0.030	0.009	0.0013

Note: $\hat{\rho} = 0.88$, likelihood ratio test = 89.8, p-value < 0.0001.

lower applications and larger variations of water occurred. In 1997 both fields were generally over-irrigated, and water would be assumed to not limit yield except on the field periphery.

Nitrate nitrogen and phosphorous (Field 1, 1997) were negatively correlated with yield, which indicates that they are not limiting. Deep Veris soil electrical conductivity was positively correlated with yield for Field 1 in 1997 and both fields in 1998. In 1997, Field 2 yield was negatively correlated with the shallow Veris soil electrical conductivity. Evidently, the conductivity data are a surrogate for soil parameters that impact crop growth. Current research is directed at identifying these soil factors and quantifying soil/conductivity relationships. The elevation parameter showed a significant relationship to yield in 1998. We assume that the elevation is also a surrogate for factors affecting yield. Organic matter in Field 1, 1997, has a positive correlation with yield.

The nitrogen values were based on pre-season soil tests, not the total available for plant growth. The average total nitrogen applied during the 1997 season was 360 and 320 kg/ha for Fields 1 and 2, respectively. The average total nitrogen applied during the 1998 season was 291 and 222 kg/ha for Fields 1 and 2, respectively. Of this total, at least one-half was applied by fertigation with the center pivot sprinkler system on both fields and years. Since more than one half of the total nitrogen was applied with the water, the water uniformity significantly influenced the nitrogen uniformity. The variability of water application would result in similar variability in nitrogen and contribute to the correlation with yield (Figure 1 and Table 1).

The nematode counts were positively correlated with yield for only Field 2 in 1997. Nematode levels for the field were low, and this predictor may be correlated with other characteristics of the field. Western bean cutworm levels were also low, the maximum

Table 5. Spatial autoregressive grain yield model coefficients for Field 2, 1997

	$\hat{\beta}$	Standard error	p-value
Intercept	12.500	0.480	<0.0001
Shallow conductivity	−0.081	0.038	0.0369
Ammonium	−0.130	0.052	0.0177
Total nematodes	0.001	0.0003	0.0395
Min. season water	0.002	0.0004	<0.0001

Note: $\hat{\rho} = 0.76$, likelihood ratio test = 38.10, p-value < 0.0001.

Table 6. Spatial autoregressive grain yield model coefficients for Field 2, 1998

	$\hat{\beta}$	Standard error	p-value
Intercept	569.000	136.000	<0.0001
Max Elevation	−0.42	0.100	0.1001
Clay content	−0.087	0.028	0.0028
WBC	−0.022	0.009	0.00159
Deep conductivity	0.200	0.026	<0.0001
K	−0.004	0.001	0.0055

Note: $\hat{\rho} = 0.83$, likelihood ratio test = 33.0, p-value < 0.0001.

for Field 2 in 1998 was 89. For this field and year, western bean cutworm counts were negatively correlated with yield.

The producers applied inputs of water, fertilizer, and pest control chemicals at levels that, they believe, do not limit yield. The significance of water application (except for Field 2 in 1998) indicates that there is a potential to reduce yield variability by increasing the uniformity of irrigation application. Even though excess water was applied, much of it came from natural precipitation that cannot be controlled. Since approximately one-half of the nitrogen was applied in the irrigation water, it also could contribute to the yield variability. The challenge is to encourage producers to experiment with reduced inputs yet not significantly increase their risk. The reduction in inputs, and hence costs, must not reduce net return for the enterprise.

The irrigation system design and operation are obvious areas to investigate to determine whether changes would reduce the standard deviation of water application and increase minimum application, thereby reducing yield variability. The minimum and maximum in the average irrigation between cells varied almost two-fold (Table 1). The coefficient of variation within a cell was 50% for Field 1 in 1997. The uniformity of water application could be improved through redesign of the sprinkler packages and operation criteria of the irrigation system. One key feature that introduces variability in a center-pivot system is the large sprinkler, described above. The large sprinkler delivers water in a much different way than the sprinklers found elsewhere in the irrigation system. Intermittent operation of the large sprinkler also introduces non-uniformity in the water distribution as the intermittent operation causes pressure changes throughout the entire system. The speed of center pivot rotation (travel speed) could be programmed to change as the large sprinkler is turned on and off. The system should be slowed down while the large sprinkler is on. This would result in sprinklers maintaining more nearly the same depth of water applied whether the end large sprinkler is on or off. Topographical differences in elevation also cause different operating pressures and thus different application depths depending on position in the field. Changing the speed of rotation should compensate for this problem, with slower speeds on the high elevation areas where the pressures are lower. Another design option is to add pressure regulators to maintain constant pressure, independent of topography or operation of the large sprinkler. However, this may significantly increase the pumping costs when the pump is supplying water at pressures higher than needed over much of the field. An economic analysis needs to be done before pressure regulators are recommended.

The temporal variability of water application is also an important consideration for improving crop production. The significance of the minimum depth of water in our analyses could indicate that certain areas received less water than required during some crop growth stages. Adoption of more scientific irrigation scheduling is an avenue that will be explored to determine whether this would decrease the variability in yield.

Farmer management strategy

The two farmer co-operators were selected because of their commitment to explore precision agriculture technology. Both farmers were using grain monitors on a combine and provided us yield data. We asked the farmers to continue to manage their operation as they had in the past. We did ask them not to apply fertilizer with a variable rate applicator. One of the farmers (Field 1) did apply fertilizer variably based on soil samples on a 1 ha grid on other fields, but was not satisfied with the application maps generated with this large grid sampling. He, with the assistance of his fertilizer dealer, became interested in developing management zones for variable application of fertilizer (Fleming, *et al.*, 1998, 1999). High, medium, and low yielding areas were delineated based on bare soil color from aerial photographs and modified with the farmer experience of yield within the field. Strips of variable rate, preplant nitrogen application were studied in 1998. The yield differences did not correlate with the preseason nitrogen treatments because the additional nitrogen applied by chemigation plus nitrogen in the profile was sufficient for maximum production. These results have led to additional studies in 1999 to determine the best nitrogen management strategy.

The 1997 observation that precipitation plus water applied exceeded the seasonal evapotranspiration (ET) by approximately 250 cm, caused both farmers to reconsider their irrigation management. Consequently, they did significantly change their irrigation management and the excess water applied (irrigation + precipitation − ET) was reduced from approximately 250 mm to 75 mm in 1998. Even though the co-operating farmers manage their fields to minimize risk, they do reduce inputs when they feel comfortable doing so. The key lesson from this example is the need to develop decision support tools that will provide producers with additional information and let them analyze the situation and change their own management strategies. Plans are being made to install new sprinkler packages to improve the uniformity in an attempt to reduce the yield variability. This is another example of the farmer analyzing the data being collected and making a decision to take positive action to correct the identified cause of yield reduction.

Both farmers are co-operating on reduced nitrogen studies on the two fields after concluding that nitrogen is being applied in excess of crop requirements. The center pivot system with a computer controlled panel makes an excellent tool for variably applying nitrogen through chemigation by sector control of the injection system. Producers are concerned about the negative impacts of chemicals on the environment and are looking at ways to match crop needs without increasing their risk beyond a manageable level and applying more chemicals than needed.

Conclusion

The potential to reduce yield variability in these semi-arid fields appears to be by increasing the uniformity of irrigation. An increase in the uniformity of water will also increase the uniformity of fertilizer and other chemicals where they are applied by chemigation. The potential benefit of increased site-specific inputs of fertility and pest management chemicals is small where the farmers' management tolerance for risk is low and inputs are high in an attempt to obtain maximum yields. The greatest potential of PF is in reducing the cost of inputs. However, PF could increase financial risk. The environmental benefits of decreased chemical inputs are an important part of management that is minimally factored into many farmer decisions and is likely to be increasingly important in the future.

The farmers have demonstrated the value of additional scientific information by changing their management strategy towards irrigation and fertilizer applications. PF provides the opportunities to decrease input costs and potentially increase net income. An important aspect of future PF research is to establish sampling strategies, analysis techniques and decision aids that can be used by producers. The current project has demonstrated the value of data collection and interpretation for each field. Farmers are moving into the information age and will be doing much of the applied research on each individual field and in management zones within a field.

Note

1. Mention of trademark, proprietary product, or vendor does not constitute a guarantee or warranty of the product by the USDA and does not imply its approval to the exclusion of other products or vendors that may also be suitable.

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